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# Knowledge based Science Target Identification System (KSTIS)

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## Abstract

A major mission driver for unmanned space exploration is to maximise science data return whilst minimising ground-based human intervention and hence associated operations costs. Future robotic exploration such as the ESA ExoMars mission (launch 2018), and the subsequent Mars Sample Return (MSR) mission will require rovers to travel further and faster than has been achieved to date. However, despite recent advancements in technology there still exists a conservative attitude towards planetary exploration. This is primarily caused by the limited number of space missions and the substantial cost of these missions. For example, the five extended mission stages of the NASA/JPL MER Rovers cost over $120,000,000; this results in substantial rewards for success and severe penalties for failure. With this in mind it is currently unlikely that a fully functional artificially intelligent autonomous system will be deployed upon an extra terrestrial planetary surface in the near future. Despite this, the recent success of the NASA/JPL MER Rovers has provided an excellent opportunity to experiment with autonomous and automatic modules on Mars. The success of these modules coupled with advancements in long range communications is leading to an increased amount of data being returned to Earth for scientific assessment. KSTIS has been designed in order to alleviate this load and also provide help in attaining assessment consistency.

## 1 Introduction

KSTIS is fuzzy knowledge based expert system; it has been designed with the aid of a planetary geologist expert. The goal is to effectively categorize the scientific value of the visible features of potential scientific targets. This is no simple task as in the field geological features often appear complex and are influenced by a high number of variables [1]. When a human geologist assesses a site, all these variables are broken down and assessed in the context of the region. These field observations can then be augmented through effective use of a hammer and a hand lens. The primary clues as to the geological background of the rock would be its structure, its texture and its composition ([1], [2], [3]). These three represent the basic ingredients for interpretation. It is unlikely that an adequate scientific evaluation could be made using only one or two of these attributes but they can be assessed independently and then their values combined. Both the process of assigning value to the targets for each attribute and combining the attribute scores is non-trivial. Dr Pullan [1] a planetary geologist expert has produced a methodology for autonomous science. In this the expert has characterized how a human geologist assesses these three attributes, and identified key aspects that autonomous science assessment systems would have to be capable of accomplishing in order to generate useful scientific output. KSTIS has been designed to implement this methodology. It has been developed as an Earth bound counterpart to the APIC (Automatic Pointing and Image Capture) [6] system. The goal of APIC is to gather HRC (High Resolution Camera) images of identified science targets in a particular scene or WAC (Wide Angle Camera) image, and then send them to Earth along with the original WAC image. The HRC images provide additional richness of information for mission scientists. KSTIS has been designed to enable scientists to properly utilize that richness. The output of KSTIS is produced in the form of a rank order list of science targets.

## 2 KSTIS Background

Current notable research conducted in this field includes the NASA/JPL Onboard Autonomous Science Investigation System (OASIS) [4] project and the CREST Autonomous Robot Scientist project (ARSP) [2]. Both these include a target assessment stage. OASIS prioritizes targets based upon their likeness to a specified signature. This signature incorporates information relating to visual texture, albedo, shape and size. The ARS project acts in a different way. It utilizes a combination of image processing techniques to identify and score specific scientific features; in this way it is similar to the way a human scientist would assess a geological scene. The ARSP project like KSTIS is based upon the methodology produced by Pullan [5, 3]. ARSP is however primarily focused upon the identification of interesting features autonomously. As the study was constrained by time and resources it demonstrated a mechanism by which science assessment could be achieved in a variety of situations using basic parameters and a simple scoring system [2]. Further work is planned to expand this study with a more representative scoring system.

KSTIS is a representative scoring system. It has been designed to emulate the way that a human geologist expert would assess a scene. In this regard similarities can be drawn between it and ARSP at a high level. However, ARSP uses a deterministic summation based method to combine science values, and is not capable of dealing with assessment uncertainty. The KSTIS system has been designed with that specific purpose in mind. The knowledge based system approach utilising fuzzy linguistic values provides an ideal way to model the uncertainty encountered during remote target assessment (i.e. assessment through use of images).

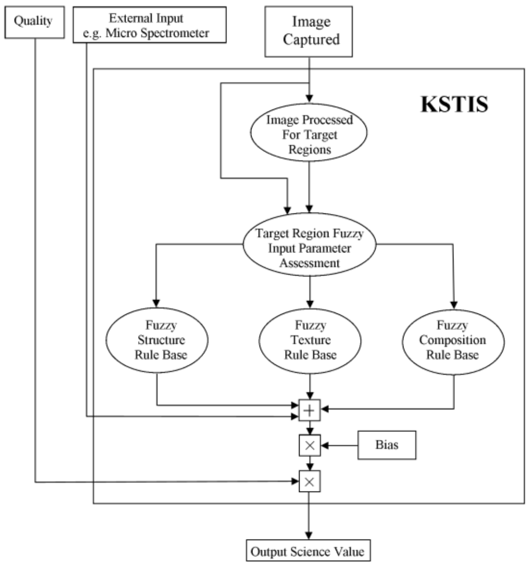


**Figure 1. KSTIS Architecture**

## 3 KSTIS Overview

Figure 1 shows an overview of the KSTIS system architecture. The knowledge based system was broken down into three subsystems, one for each of the basic ingredients for interpretation as identified by the domain expert [1]. A user interface feeds data into these subsystems independently. The results could be retrieved discreetly from the three subsystems, but at this point it is of little use as it is the composite of the three scores, along with the quality and bias factor, which gives a meaningful science value. The quality value is an indicator of the quality of the image; this could be adjusted if the image was out of focus or if a reflection on the lens deteriorated the quality of the image. The bias factor could be adjusted in order to increase the final scientific value or to decrease it dependant on the mission contextual model. For example if a target was processed and received a low scientific value, but according to the contextual model, this target could be a potentially valuable target, then the bias input could be used by an expert to increase the target's score.

## 4 Target Identification

The first step within KSTIS is to identify potential science targets. The rock detection software developed for APIC was employed to accomplish this [6]. This is a region growing algorithm which has been designed to be as efficient as possible but was not designed with target assessment in mind. As a result of this it is possible that sections of the target may be missed, resulting in the identified region not encompassing the entire target. However, as at this stage the KSTIS input is generated by a human user, the accuracy of the detected targets is of less importance as it can be augmented by a user's ability to define the target boundary. In this case the rock detection algorithm is used as a first pass to identify the targets to be assessed and labels them with an ID. The image output by this software can be seen in figure 2. This image is then shown to the user along with the HRC images of the target regions for the "target region fuzzy input parameter assignment" stage.

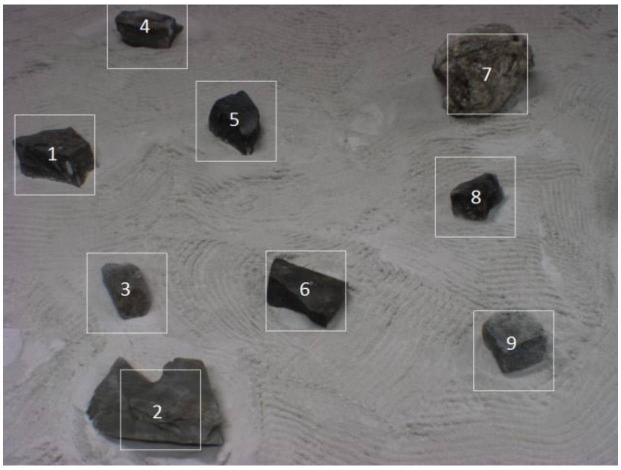


**Figure 2. AU laboratory image of potential science targets identified and labelled by APIC**

## 5 Science assessment

The implemented rules and membership functions have been developed through extensive collaboration with our domain expert. This has led to a group of membership functions which best model the way that the expert's interest in certain features develops. The four different typed of membership function used within KSTIS are (see figure 3):

• Triangular functions. These are used when the expert's interest in a feature steadily rises, briefly peeks and then drops off steadily. For example, if bedding with a thickness of 10 mm is interesting, the expert's interest may steadily increase between 8-9.9 mm and then steadily decrease between 10.1-12 mm.

• Trapezoidal functions. These were used when a range of inputs could be viewed as satisfying the membership criteria; for example thin lamination can range from 2 – 3 mm.

• Gaussian functions. These model an input that has one 'fully' satisfying value and outside of that value the degree of membership degrades slowly.

• Bell functions. These are similar to Gaussian functions in the steady incline and decline but they were used when a larger range of values satisfied the criteria. For example when looking for the colour red (using HSL), a range of H values are perceived as red to the observer. This redness then fades as the colour changes.

Rules were developed in a similar way, i.e. during collaboration a quantification of the SV of certain geological features was produced (based upon the ESA ExoMars science goals).

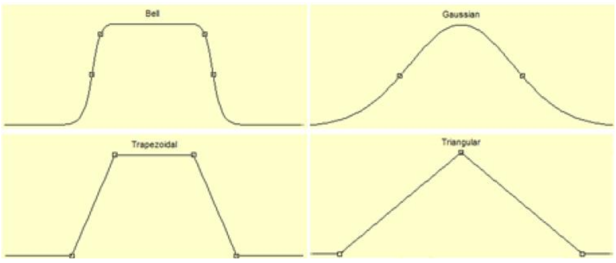


**Figure 3. The four types of membership function used during the design and implementation of KSTIS; Top left: Bell shaped, Top right: Gaussian, Bottom left: Trapezoidal, Bottom right: Triangular**

KSTIS utilises three rule bases to carry out a science assessment. The features used by KSTIS within these rule bases, represent a subset of the features identified by the domain expert [1]. During early consultation with the domain expert it was agreed that a subset of the identified features would be used to reduce the complexity of the system and act as a proof of concept. The selection process was undertaken with the help of the expert and based upon the relevance of the feature at the target scale (which was between 2-10 m from the camera), the complexity of identification, and its relevance to science value.

### 5.1 Structure

Three features have been selected for processing by the system as regards structure:

- The presence of bedding: a true/false input which indicates if bedding was observed in the image being assessed.
- Scale: a measure of the thickness of the bedding observed. The value was required in mm.
- Type: an indication of the "curviness" of the observed bedding. This feature was assessed on a sliding scale from planar to curvy.

### 5.2 Texture

Three features have been selected for processing by the system as regards texture:

- Surface lustre: This is a measure of surface glossiness of the observed target.
- Relief: a measure of the roughness of the surface texture observed. This value ranges from rough to smooth.
- Rock shape: an indication of the roundness of the observed rock. This value ranges from angular to very round through rounded.

### 5.3 Composition

Four features have been selected, for processing by the system as regards composition:

- Hue: the colour of the target. Forms part of the HSV colour space.
- Albedo: a measure of the reflectivity of the observed target.
- Whiteness: a measure of the whiteness of the observed target.
- Hue present: a Boolean input to indicate if the hue is indeterminable (meaning target is white, gray or black).

### 5.4 Science value

Each of the three subsystems utilise Mamdani's fuzzy inference method [7], a number of membership functions, and a collection of rules. The combined output is then de-fuzzified using Centre of Gravity (COG) de-fuzzification. This returns a crisp number which represents a rock's SV (Science Value).

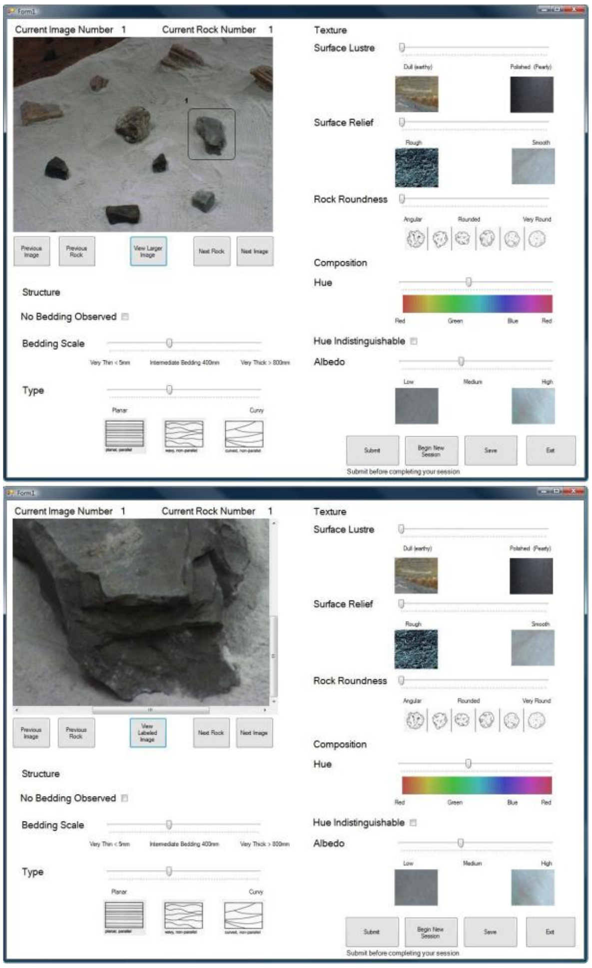


**Figure 4. The KSTIS user interface. Top: User interface showing wide angled image providing target context. Bottom: User interface showing HRC image providing fine detail.**

## 6 User Interface

The KSTIS user interface can be seen in figure 4. The interface is windows based and has been built with the .net framework. It can be broken down into five parts;

1. The image and image control buttons: Top left of the user interface indicates the current image number in the sequence being processed, and the rock number in the image being assessed. The WAC image is displayed below this by default. Five control buttons relating to the image navigation are located just under the image. These allow the user to navigate back and forwards through the sequence of images and between rocks within the images. The central button “view larger image” display the APIC captured HRC image in place of the WAC image.

2. Structure inputs: The bottom left of the interface contain the three structure inputs. A tick-box for the Boolean input relating to the presence or absence of observed bedding and two sliders, one for the scale of bedding and the other for the type of bedding. Both of these are set to zero and disabled if no bedding is observed.

3. Texture inputs: Located in the top right corner of the interface. This contains three sliders relating to the lustre, relief and roundness inputs of the texture rule base.

4. Composition inputs: The centre right side of the interface contained two sliders which represented the hue and albedo inputs of the composition rule base and a tick box which indicates whether the hue of the object was indeterminable.

5. Session control buttons: located at the bottom right hand corner. “Submit” opens a file save dialogue and asked for a name and location to save the output file to. The “Begin new session” button zeroes all input values stored in the current session. “Save” writes the session data to a temporary file that will be loaded next time the application is opened. “Exit” saves the current session and then closes the application.

## 7 Experimental Setup

Had KSTIS been a full implementation of the expert’s methodology for autonomous science, the logical experiment would have been to ask several experts to assess the rock scene both in person and then remotely and then compare their results to the ones generated by KSTIS. However, the KSTIS preliminary system does not fully implement the methodology put forward by the expert, only a subset of the features are being assessed. Thus a like for like comparison between the expert and KSTIS would be of limited use at this stage. Instead it was decided that the system would be tested in a mission like scenario. During each experiment an initial WAC image was presented to a subject with ten rock targets identified and labelled. Ten subjects then provided experimental input for each image. The inputs were processed by KSTIS and the resultant SV for each rock was generated. These targets were then ranked according to the KSTIS generated SV scores. In order to adequately test the KSTIS operations tool, six experiments have been undertaken. Each experiment involved fully exercising KSTIS in a “mission like” context. After all experimentation was completed and the rank orders produced, they were statistically analysed for correlation, to examine the level of agreement that existed between the expert and the 9 subjects. These experiments have been undertaken to prove that KSTIS is capable of producing scientifically consistent results and that the 9 subject's assessments show strong likenesses to the experts.

The subjects were all computer literate adults between the age of 27 and 55. The experimentation was carried out through use of the KSTIS user interface (see figure 4). Aberystwyth's ExoMars PanCam emulator was used to capture the majority of the images used during the experimentation. The only exception to this was the Martian image used. This composite image was produced by combining a number of MER images.

During the experiment, the subjects were provided with guidance notes in the form of two documents. These documents outlined the basic procedure of the experiment and provided the subjects with an explanation of the technical terms used. A selection of example classifications was also provided in an attempt to provide some reference values to unify the trials. Subjects were also instructed to view each image as an independent experiment. Therefore rocks viewed in multiple images were to be scored independently. The software was made available for subjects to run on their own computers. The interface required a ".net" enabled Microsoft Windows operating system. UNIX subjects were able to access the system through a virtual desktop environment. No attempt was made to unify display settings or to control the size and quality of the display that the assessment was made on.

## 8 Experiments set 1 results and discussion

Spearman's rank order assessment [15] was carried out on the rank orders produced by the users and the expert. This statistical analysis did not identify a strong correlation between all results. Given that the scores generated by the domain expert are being used as the "control" rank order, then a positive result would have been achieved if all subjects had a correlation coefficient greater then 0.5, and a one-sided significance of 0.05 or less. Only 22% of the subjects achieved this in experiment one, 11% in experiment two, 33% experiment three, 44% experiment four, 22% experiment five and 44% in experiment six. These disappointing results led to further analysis in an attempt to discover what was causing the divergent results, and what improvements might be necessary to achieve the desired results.

From an examination of the obtained results, disagreements between the subjects were observed, and two problems were clearly identified. Firstly there was a lack of consistency during the use of the "colour indistinguishable" and secondly, the "no bedding observed" tick-box. These two inconsistencies have in some cases, significantly altered the generated SV.

### 8.1 Problems caused by composition input

The composition fuzzy rule base requires three inputs from the user, hue (colour), albedo and a flag indicating an indistinguishable colour. The fuzzy system processes four inputs. If the "colour indistinguishable" tick-box is ticked, a whiteness value is derived from the input albedo value. Humans are not well equipped to distinguish colours and reflectance properties in unknown domains. Substantial research has been conducted in the field of neuroscience regarding the way that humans interpret colours [8], texture [9] and brightness [10]. Whilst human visual perception is beyond the scope of this research, several methodologies put forward in the literature have provided clues as to how this problem could be alleviated or even overcome. Initially an image mask could be produced to allow the user to view the target in isolation from its surrounding objects, shapes and colours. This would alleviate some of the visual illusions introduced by problems such as the "Adelson's Checker shadow illusion" [9]. Unfortunately, the use of an image mask would not alleviate all problems introduced from human visual perception. Other problems such as the human perception of materials (and the assumptions that result from this classification) can have impact on how a target is scored and how it is assessed.

However, computers are not affected by the (in the most part) beneficial affects introduced by human visual perception. It is also possible for a computer to identify the hue of a target when an excess or shortage of light makes the hue indistinguishable to a human. It would be desirable to aid the human user with computer generated cues, or even replace the KSTIS composition input by a computer generated measure of hue and brightness.

### 8.2 Problems caused by structure inputs

The structure rule base of the KSTIS system requires three inputs; scale, type of bedding and if bedding is in fact present. The difficulty has been identified as arising from the identification of the presence of bedding. In one case the expert identified planar bedding, with a scale of approximately 4mm when other subjects identified no bedding. This is challenging as not all of the lines visible on a target's surface represent sedimentary structure. The fuzzy system has been designed with the domain expert to allow for variations in user inputs due to experience or personal biases. This has been accomplished by ensuring that the science values transition slowly, from high to low. This provides scope for some input inaccuracies without diminishing the value of the expert system. This results in a smoothing of results and helps alleviate inaccuracies in observation causing substantial swings in value. However, this is not possible with the "bedding present" input. If the bedding present tick-box is ticked the target will achieve no score for structure. If this is an error, it will result in a significant reduction in the targets SV.

Computational input could be used to aid in the measuring of bedding. If a user could identify two bedding lines the computer could calculate the distance between the two lines. In order to accomplish this, the distance to the object would need to be known. ARSP has begun to address the automatic identification of bedding [2]. It is a non-trivial problem and is yet to be fully solved.

### 8.3 Computational input

Computational input was identified as a method of reducing the errors introduced by the human perception of colour and brightness on the compositional rule base, thus reducing SV variations. Variations were exaggerated partially by the substantial value attributed to a target displaying a blue hue by the expert. MatLab functions were designed to pre-process marked areas and calculate the average greyscale and hue of the target. The greyscale value is being used as an estimation of reflectance and is directly mapped to albedo. The hue however presents a more challenging problem, as a target is made up of a combination of pixels each having their own value. An initial solution was developed, where the pixels in each target were split into three categories; Red, Green and Blue. The number of pixels in each category was counted, and the colour with the highest science value that contains a hundred or more pixels was chosen to represent the target. The average hue of the pixels within that group was then assigned as the hue of the target. This approach should not to be considered as a final solution.

## 9 Experiments set 2 results and discussion

Automatic computational input was included and a far higher correlation has been achieved during this round of experiments between all of the results. Again, the control results were generated by the domain expert. During the first set of experiments only 22% achieved a strong correlation in experiment one, 11% in experiment two, 33% experiment three, 44% experiment four, 22% experiment five and 44% in experiment six. These results have been greatly improved during the second set of experiments. During these experiments 100% achieved a strong correlation with the expert in experiment one, 67% in experiment two, 22% in experiment three, 44% in experiment four, 67% in experiment five and 89% in experiment six. The results are still not ideal but represent a substantial improvement in correlation. They show substantial improvements, not only in the number achieving a correlation coefficient of 0.5 or above, but in the strength of the correlations achieved. In some cases these coefficients are now approaching one.

Clearly any user input inconsistency results in inconsistency in the generated SV. It is currently unclear how much of this inconsistency has been introduced by problems with the user interface (see figure 4). The current user interface utilises several sliders to capture user's assessments of target attributes. Sliders are not an accurate way of capturing information such as this, and may be the source of some erroneous entries. For example, subject five identified bedding with a thickness of 88 mm for rock number ten in experiment one, compared with the experts figure of 4 mm. This is not an isolated case and represents an additional slider movement of only a few mm.

The domain expert's experience of identifying bedding and lamination in rock formations also has an impact. A number of examples have been observed where the expert has either identified subtle bedding when a number of subjects missed it, or dismissed possible bedding when a number of other subjects identified it. The only way to improve this situation is to provide additional training, practise and example images for novice users. The quality of the images provided to users is also a factor in the assessment of science value. The expert has gathered a great deal of experience in assessing science targets in a remote environment through use of images and contextual information [11, 1]. The other subjects who took part in the experimentation did not have this level of experienced perception or background knowledge.

## 10 CONCLUSIONS AND FUTURE WORK

KSTIS has been designed as a complementary system to APIC in that it aids in the processing of the increased number of scientific images down-linked by the APIC system. KSTIS is a ground-based science target assessment tool. Scientific assessment is achieved through the implementation of the methodology for autonomous science proposed by [1]. It has been enabled through use of a combination of three fuzzy rule bases, one representing each of the three components used in geological interpretation. The tool has been designed to provide an intuitive interface for users to assess the images returned by the APIC system. KSTIS generates a resultant scientific value based upon the assessment of APIC images by the user, and creates a rank order list of the targets according to their scientific value. This evaluation can then be used to aid in the final decision of which targets to investigate further. KSTIS experimentation has highlighted that it is not only necessary to faithfully emulate a human expert's knowledge but also their perception. A human geologist would spend years developing visual skills and honing their perception of the environment for use during field expeditions. The introduction of image processing routines capable of identifying geological features could make this possible. Input to the composition fuzzy logic rule base was identified as the primary cause for interpretation errors. Image processing subroutines were designed and included to replace these inconsistent inputs. The result was a strengthening in correlation of the output scores. This has added to the argument to fully automate the feature assignment stage. The automation of this stage would be necessary should APIC and the KSTIS systems be fully integrated to produce an autonomous science target selection system, which could be deployed on-board an autonomous rover platform. This has been designated as future work, and beyond the scope of this study. In summary, the combination of the on-board APIC system and the ground-based KSTIS system represents a novel move towards increasing the acceptability and technology readiness of a fully integrated autonomous rover, with the ability to make target selections based on geological assessment.

## 10.1 Enhancements and recommendations for future research

Image segmentation research being conducted by Shang [12] is currently being adapted to identify rocks in a Martian terrain. This research offers a potential replacement to the region growing algorithm currently employed. Improved rock identification results have been demonstrated using this implementation (see figure 5). An interesting aspect of this research is its ability to distinguish between rock types and regions within rocks. This is beneficial and could be used to distinguish regions within a larger target [13].

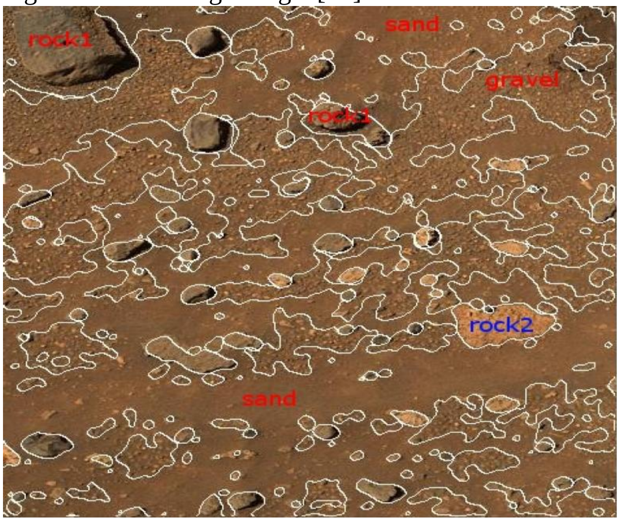


**Figure 5. This image is classified using the Fuzzy-Rough Feature Selection approach, being researched at Aberystwyth University [13].**

### 10.1.1 Feature detection and classification

During the experimentation of the KSTIS system, a need for image processing routines to identify input features was identified. These routines would need to emulate the perception of a human expert. Some work has been carried out towards this end during the ARS project ([2, 5, 14]). Further work is still necessary in order to fully automate the process of target science assessment.

### 10.1.2 Enhanced KSTIS knowledge base

The current KSTIS system has been produced to prove the concept of fuzzy knowledge based target classification. Initially, only a subset of the science features identified by the expert during the knowledge elicitation stage were implemented in order to reduce complexity and enhance system transparency. A natural progression would be to include more features in an enhanced knowledge base.

### 10.1.3 Integration of other instruments into the KSTIS system

KSTIS has currently been developed to work with images gathered by an HRC, similar to the one found on ExoMars. Future work would be to enable KSTIS assessments from other instruments such as the images captured by the CLUPI instrument. The change in input would require a new set of SV to be developed by the planetary geology expert and the knowledge engineer.

### 10.1.4 Enhanced user interface

During the KSTIS experimentation problems were identified with the current user interface. Primarily the use of tick-boxes and the fine scale on the sliders. A good example is the structure slider “scale”. Small movements were required to properly label targets. It is intended that the system will be re-implemented, and a web interface produced.

### 10.1.5 Inclusion of multi-spectral camera information to KSTIS

The WAC cameras on the ExoMars rover will be fitted with a number of multi-spectral filters. These filters can be used to recover spectra from targeted regions and in some cases this can be used to interpret the composition of the target. This information could provide much useful information during the science assessment stage.

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